

Resource Allocation for Coordinated Multipoint Networks with Wireless Information and Power Transfer

Derrick Wing Kwan Ng and Robert Schober*

Institute for Digital Communications

Friedrich-Alexander-University Erlangen-Nürnberg (FAU), Germany

Abstract—This paper studies the resource allocation algorithm design for multiuser coordinated multipoint (CoMP) networks with simultaneous wireless information and power transfer (SWIPT). In particular, remote radio heads (RRHs) are connected to a central processor (CP) via capacity-limited backhaul links to facilitate CoMP joint transmission. Besides, the CP transfers energy to the RRHs for more efficient network operation. The considered resource allocation algorithm design is formulated as a non-convex optimization problem with a minimum required signal-to-interference-plus-noise ratio (SINR) constraint at multiple information receivers and a minimum required power transfer constraint at the energy harvesting receivers. By optimizing the transmit beamforming vectors at the CP and energy sharing between the CP and the RRHs, we aim at jointly minimizing the total network transmit power and the maximum capacity consumption per backhaul link. The resulting non-convex optimization problem is NP-hard. In light of the intractability of the problem, we reformulate it by replacing the non-convex objective function with its convex hull, which enables the derivation of an efficient iterative resource allocation algorithm. In each iteration, a non-convex optimization problem is solved by semi-definite programming (SDP) relaxation and the proposed iterative algorithm converges to a local optimal solution of the original problem. Simulation results illustrate that our proposed algorithm achieves a close-to-optimal performance and provides a significant reduction in backhaul capacity consumption compared to full cooperation. Besides, the considered CoMP network is shown to provide superior system performance as far as power consumption is concerned compared to a traditional system with multiple antennas co-located.

I. INTRODUCTION

Next generation wireless communication networks are required to provide ubiquitous and high data rate communication with guaranteed quality of service (QoS). These requirements have led to a tremendous need for energy in both transmitter(s) and receiver(s). In practice, portable mobile devices are typically powered by capacity limited batteries which require frequent recharging. Besides, battery technology has developed very slowly over the past decades and the battery capacities available in the near future will be unable to improve this situation. Consequently, energy harvesting based mobile communication system design has become a prominent approach for addressing this issue. In particular, it enables self-sustainability for energy limited communication networks. In addition to conventional energy harvesting sources such as solar, wind, and biomass, wireless power transfer has been proposed as an emerging alternative energy source, where the receivers scavenge energy from the ambient radio frequency (RF) signals [1]–[3]. In fact, wireless power transfer technology not only eliminates the need of power cords and chargers, but also

facilitates one-to-many charging due to the broadcast nature of wireless channels. More importantly, it enables the possibility of simultaneous wireless information and power transfer (SWIPT) leading to many interesting and challenging new research problems which have to be solved to bridge the gap between theory and practice. In [1], the authors investigated the fundamental trade-off between harvested energy and wireless channel capacity across a pair of coupled inductor circuit in the presence of additive white Gaussian noise. Then, in [2], the study was extended to multiple antenna wireless broadcast systems. In [3], the energy efficiency of multi-carrier systems with SWIPT was revealed. Specifically, it was shown in [3] that integrating an energy harvester into a conventional information receiver improves the energy efficiency of a communication network. The results in [1]–[3] indicate that both the information rate and the amount of harvested energy at the receivers can be significantly increased at the expense of an increase in the transmit power. However, despite the promising results in the literature, the performance of wireless power/energy transfer systems is still limited by the distance between the transmitter and the receiver due to the high signal attenuation associated with path loss.

Coordinated multipoint (CoMP) transmission is an important technique for extending service coverage, improving spectral efficiency, and mitigating interference [4]–[8]. A possible deployment scenario for CoMP networks is to split the functionalities of the base stations between a central processor (CP) and a set of remote radio heads (RRHs). In particular, the CP performs the power hungry and computationally intensive baseband signal processing while the RRHs are responsible for all radio frequency (RF) operations such as analog filtering and power amplification. Besides, the RRHs are distributed across the network and connected to the CP via backhaul links. This system architecture is known as cloud computing network. As a result, the CoMP systems architecture inherently provides spatial diversity for combating path loss and shadowing. It has been shown that a significant system performance gain can be achieved when full cooperation is enabled in CoMP systems [4], [5]. However, in practice, the enormous signalling overhead incurred by the information exchange between the CP and the RRHs may be infeasible when the capacity of the backhaul link is limited. Hence, resource allocation for CoMP networks with finite backhaul capacity has attracted much attention in the research community [6]–[8]. In [6], the authors studied the energy efficiency of CoMP multi-cell networks with capacity constrained backhaul links. In [7] and [8], iterative sparse beamforming algorithms were proposed to reduce the load of the backhaul links while providing reliable communication to the users. However, the energy sources of the receivers in

*The author is also with the University of British Columbia.

[4]–[8] were assumed to be perpetual and this assumption may not be valid for power-constrained portable devices. On the other hand, the signals transmitted by the RRHs could be exploited for energy harvesting by the power-constrained receivers for extending their lifetimes. However, the resource allocation algorithm design for CoMP SWIPT systems has not been solved so far, and will be tackled in this paper.

Motivated by the aforementioned observations, we formulate the resource allocation algorithm design for multiuser CoMP communication networks with SWIPT as a non-convex optimization problem. We jointly minimize the total network transmit power and the maximum capacity consumption per backhaul link while ensuring quality of service (QoS) for reliable communication and efficient wireless power transfer. In particular, we propose an iterative algorithm which provides a local optimal solution for the considered optimization problem.

II. SYSTEM MODEL

A. Notation

We use boldface capital and lower case letters to denote matrices and vectors, respectively. \mathbf{A}^H , $\text{Tr}(\mathbf{A})$, and $\text{Rank}(\mathbf{A})$ represent the Hermitian transpose, trace, and rank of matrix \mathbf{A} ; $\mathbf{A} \succ \mathbf{0}$ and $\mathbf{A} \succeq \mathbf{0}$ indicate that \mathbf{A} is a positive definite and a positive semidefinite matrix, respectively; $\text{vec}(\mathbf{A})$ denotes the vectorization of matrix \mathbf{A} by stacking its columns from left to right to form a column vector; \mathbf{I}_N is the $N \times N$ identity matrix; $\mathbb{C}^{N \times M}$ denotes the set of all $N \times M$ matrices with complex entries; \mathbb{H}^N denotes the set of all $N \times N$ Hermitian matrices; $\text{diag}(x_1, \dots, x_K)$ denotes a diagonal matrix with the diagonal elements given by $\{x_1, \dots, x_K\}$; $|\cdot|$ and $\|\cdot\|_p$ denote the absolute value of a complex scalar and the l_p -norm of a vector, respectively. In particular, $\|\cdot\|_0$ is known as the l_0 -norm of a vector and denotes the number of non-zero entries in the vector; the circularly symmetric complex Gaussian (CSCG) distribution is denoted by $\mathcal{CN}(\mu, \sigma^2)$ with mean μ and variance σ^2 ; \sim stands for “distributed as”; $\lceil x \rceil$ is the ceiling function denoting the smallest integer not smaller than x .

B. CoMP Network Model and Central Processor

We consider a CoMP multiuser downlink communication network. The system consists of a CP, L RRHs, K information receivers (IRs), and M energy harvesting receivers (ERs), cf. Figure 1. Each RRH is equipped with $N_T > 1$ transmit antennas. The IRs and ERs are single antenna devices which exploit the received signal powers in the RF for information decoding and energy harvesting, respectively. In practice, the ERs may be idle IRs which are scavenging energy from the RF for extending their lifetimes. On the other hand, the CP is the core unit in the network. In particular, it has the data of all information receivers. Besides, we assume that the global channel state information (CSI) is perfectly known at the CP and all computations are performed in this unit. Based on the available CSI, the CP computes the resource allocation policy and broadcasts it to all RRHs. Specifically, each RRH receives the control signals for resource allocation and the data of the K IRs from the CP via a backhaul¹ link. Furthermore, we assume that the CP supplies energy to the RRHs in the network via dedicated power lines to support the RRHs’ power consumption.

C. Channel Model

We focus on a frequency flat fading channel and a time division duplexing (TDD) system. Each RRH obtains the local

¹In practice, the backhaul links can be implemented by different technologies such as digital subscriber line (DSL) or out-of-band microwave links.

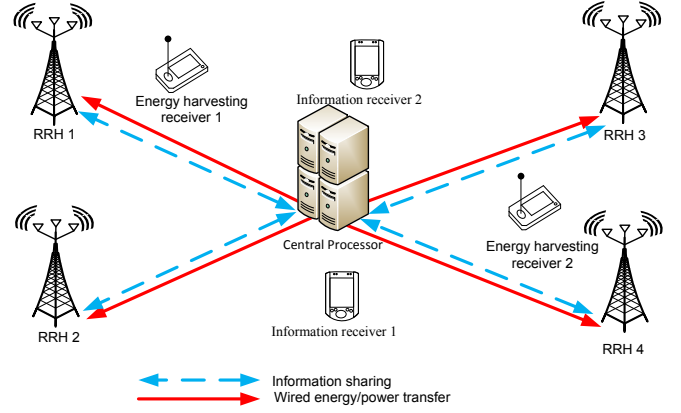


Fig. 1. Coordinated multipoint (CoMP) multiuser downlink communication system model with a central processor (CP), $L = 4$ remote radio heads (RRHs), $K = 2$ information receivers (IRs), and $M = 2$ energy harvesting receiver (ERs).

CSI of all receivers by exploiting channel reciprocity and handshaking signals. Subsequently, the RRHs feed their local CSI to the CP for computation of the resource allocation policy. The received signals at IR $k \in \{1, \dots, K\}$ and ER $m \in \{1, \dots, M\}$ are given by

$$y_k^{\text{IR}} = \underbrace{\mathbf{h}_k^H \mathbf{x}_k}_{\text{desired signal}} + \underbrace{\sum_{j \neq k}^K \mathbf{h}_k^H \mathbf{x}_j}_{\text{multiple-access interference}} + n_k^{\text{IR}}, \quad (1)$$

$$y_m^{\text{ER}} = \mathbf{g}_m^H \sum_{k=1}^K \mathbf{x}_k + n_m^{\text{ER}}, \quad (2)$$

where $\mathbf{x}_k \in \mathbb{C}^{N_T \times 1}$ denotes the joint transmit signal vector of the L RRHs to IR k . The channel between the L RRHs and IR k is denoted by $\mathbf{h}_k \in \mathbb{C}^{N_T \times 1}$, and we use $\mathbf{g}_m \in \mathbb{C}^{N_T \times 1}$ to represent the channel between the L RRHs and ER m . We note that the channel vector captures the joint effects of multipath fading and path loss. $n_k^{\text{IR}} \sim \mathcal{CN}(0, \sigma_s^2)$ and $n_m^{\text{ER}} \sim \mathcal{CN}(0, \sigma_s^2)$ are additive white Gaussian noises (AWGN). We assume that the noise variances, σ_s^2 , are identical at all receivers.

D. Signal Model and Backhaul Model

In each scheduling time slot, K independent signal streams are transmitted simultaneously to the K IRs. Specifically, a dedicated beamforming vector, $\mathbf{w}_k^l \in \mathbb{C}^{N_T \times 1}$, is allocated to IR k at RRH $l \in \{1, \dots, L\}$ to facilitate information transmission. For the sake of presentation, we define a super-vector $\mathbf{w}_k \in \mathbb{C}^{N_T L \times 1}$ for IR k as

$$\mathbf{w}_k = \text{vec}([\mathbf{w}_k^1 \mathbf{w}_k^2 \dots \mathbf{w}_k^L]). \quad (3)$$

\mathbf{w}_k represents a joint beamformer used by the L RRHs for serving IR k . Then, \mathbf{x}_k can be expressed as

$$\mathbf{x}_k = \mathbf{w}_k s_k, \quad (4)$$

where $s_k \in \mathbb{C}$ is the data symbol for IR k and $\mathcal{E}\{|s_k|^2\} = 1, \forall k \in \{1, \dots, K\}$, is assumed without loss of generality.

On the other hand, the data of each IR is delivered from the CP to the RRHs via backhaul links. The backhaul capacity consumption for backhaul link $l \in \{1, \dots, L\}$ is given by

$$C_l^{\text{Backhaul}} = \sum_{k=1}^K \left\| \left[\|\mathbf{w}_k^l\|_2 \right] \right\|_0 R_k, \quad (5)$$

where R_k is the required backhaul data rate for conveying the data of IR k to a RRH. We note that the backhaul links may be capacity-constrained and the CP may not be able to send the data to all RRHs as required for full cooperation. Thus, to reduce the load on the backhaul links, the CP can enable partial cooperation by sending the data of information receiver k only to a subset of the RRHs. In particular, by setting $\mathbf{w}_l^k = \mathbf{0}$, RRH l is not participating in the joint data transmission to IR k . Thus, the CP is not required to send the data for IR k to RRH l via the backhaul link which leads to a lower backhaul link capacity consumption.

E. RRH Power Supply Model

In the considered CoMP network, we assume that the CP transfers energy to the RRHs for supporting the power consumption at the RRHs and facilitating a more efficient network operation. In particular, $E_l^s \beta_l$ units of energy are transferred to RRH l via a dedicated power line where $E_l^s, \forall l \in \{1, \dots, L\}$, is the power supplied by the CP to RRH l . $0 \leq \beta_l \leq 1$ is the fraction of power that arrives at RRH l ; $1 - \beta_l$ denotes the power loss coefficient for the power loss in delivering the power from the CP to RRH l .

III. PROBLEM FORMULATION

A. Channel Capacity and Energy Harvesting

The channel capacity (bit/s/Hz) between the L RRHs and IR k is given by

$$C_k = \log_2(1 + \Gamma_k), \text{ where } \Gamma_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_s^2} \quad (6)$$

is the receive signal-to-interference-plus-noise ratio (SINR) at IR k .

On the other hand, the information signal, $\mathbf{w}_k s_k, \forall k \in \{1, \dots, K\}$, serves as a dual purpose carrier for conveying both information and energy concurrently in the considered system. The total amount of energy² harvested by ER $m \in \{1, \dots, M\}$ is given by

$$E_m^{\text{ER}} = \mu \left(\sum_{k=1}^K |\mathbf{g}_m^H \mathbf{w}_k|^2 \right), \quad (7)$$

where $0 < \mu \leq 1$ denotes the efficiency of the conversion of the received RF energy to electrical energy for storage. We assume that μ is a constant and is identical for all ERs. Besides, the contribution of the antenna noise power to the harvested energy is negligibly small compared to the harvested energy from the information signal, $|\mathbf{g}_m^H \mathbf{w}_k|^2$, and thus is neglected in (7).

B. Optimization Problem Formulation

The system objective is to jointly minimize the weighted sum of the total network transmit power and the maximum capacity consumption per backhaul link while providing QoS for reliable communication and power transfer. The resource allocation algorithm design is formulated as the following optimization

problem:

$$\begin{aligned} & \underset{E_l^s, \mathbf{w}_k}{\text{minimize}} \quad \delta \max_{l \in \{1, \dots, L\}} \left\{ C_l^{\text{Backhaul}} \right\} + \eta \sum_{k=1}^K \sum_{l=1}^L \|\mathbf{w}_k^l\|_2^2 \\ & \text{s.t.} \quad \text{C1: } \Gamma_k \geq \Gamma_{\text{req}_k}, \quad \forall k, \\ & \quad \text{C2: } P_C^{\text{CP}} + \sum_{l=1}^L E_l^s \leq P_{\text{max}}^{\text{CP}}, \\ & \quad \text{C3: } P_{C_l} + \varepsilon \sum_{k=1}^K \|\mathbf{w}_k^l\|_2^2 \leq E_l^s \beta_l, \quad \forall l, \\ & \quad \text{C4: } \sum_{k=1}^K \|\mathbf{w}_k^l\|_2^2 \leq P_l^{\text{Tmax}}, \quad \forall l, \\ & \quad \text{C5: } E_m^{\text{ER}} \geq P_m^{\text{min}}, \quad \forall m, \quad \text{C6: } E_l^s \geq 0, \quad \forall l, \end{aligned} \quad (8)$$

where $\delta \geq 0$ and $\eta \geq 0$ in the objective function are constants which reflect the preference of the system operator for the capacity consumption of individual backhaul links and the total network transmit power consumption, respectively. Besides, δ can also be interpreted as the energy/power cost in conveying information to the RRHs via backhaul. $\Gamma_{\text{req}_k} > 0$ in constraint C1 indicates the required minimum receive SINR at IR k for information decoding. The corresponding data rate per backhaul link use for IR k is given by $R_k = \log_2(1 + \Gamma_{\text{req}_k})$. In C2, P_C^{CP} and $P_{\text{max}}^{\text{CP}}$ are the hardware circuit power consumption and the maximum power available at the CP, respectively. In C3, P_{C_l} and $E_l^s \beta_l$ are the hardware circuit power consumption and the maximum available power at RRH l , respectively. $\varepsilon \geq 1$ is a constant which accounts for the power inefficiency of the power amplifier. P_l^{Tmax} in C4 is the maximum transmit power allowance for RRH l , which can be used to limit out-of-cell interference. Constant P_m^{min} in constraint C5 specifies the required minimum harvested energy at ER m . C6 is the non-negativity constraint on the power optimization variables.

Remark 1: We note that the objective function considered in this paper is different from that in [7] and [8]. In particular, we focus on the capacity consumption of individual backhaul links while [7] and [8] studied the total network backhaul capacity consumption. Although the considered problem formulation does not constrain the capacity consumption of the individual backhaul links, it provides a first-order measure of the backhaul loading in the considered CoMP network when enabling partial cooperation. This information provides system design insight for the required backhaul deployment.

IV. RESOURCE ALLOCATION ALGORITHM DESIGN

The optimization problem in (8) is a non-convex problem due to the non-convexity of the objective function, constraint C1, and constraint C5. In particular, the combinatorial nature of the objective function results in an NP-hard optimization problem [7]. To strike a balance between system performance and computational complexity, we develop an iterative algorithm for obtaining a suboptimal solution. To this end, we first reformulate the optimization problem by approximating the original non-convex objective function as a weighted sum of convex functions with different weight factors. Then, we recast the reformulated problem as a semidefinite programming (SDP) problem via SDP relaxation and solve it optimally. Subsequently, a suboptimal solution to the original optimization problem is obtained by updating the weight factors and solving the reformulated problem iteratively.

²We adopt the normalized energy unit Joule-per-second in this paper. Therefore, the terms “power” and “energy” are used interchangeably.

A. Convex Relaxation

The non-convex weighted capacity consumption of backhaul link l , $\delta C_l^{\text{Backhaul}}$, can be approximated as follows:

$$\begin{aligned} \delta C_l^{\text{Backhaul}} &\stackrel{(a)}{=} \delta \sum_{k=1}^K \left\| \left[\|\mathbf{w}_k^l\|_2^2 \right] \right\|_0 R_k \\ &\stackrel{(b)}{\approx} \delta \sum_{k=1}^K \left\| \left[\rho_k^l \|\mathbf{w}_k^l\|_2^2 \right] \right\|_1 R_k = \delta \sum_{k=1}^K \rho_k^l \|\mathbf{w}_k^l\|_2^2 R_k \end{aligned} \quad (9)$$

where $\rho_k^l \geq 0, \forall k, l$, in (b) are given constant weight factors which can be used to achieve solution sparsity. (a) indicates that the value of the l_0 -norm is invariant when the input arguments are squared. (b) is due to the fact that the l_0 -norm can be approximated by its convex hull which is the l_1 -norm. This approximation is known as convex relaxation and is commonly used in the field of compressed sensing for handling l_0 -norm optimization problems [7]–[10].

B. SDP Relaxation

We substitute (9) into (8) and define $\mathbf{W}_k = \mathbf{w}_k \mathbf{w}_k^H$, $\mathbf{H}_k = \mathbf{h}_k \mathbf{h}_k^H$, and $\mathbf{G}_m = \mathbf{g}_m \mathbf{g}_m^H$. Then, we recast the reformulated problem in its epigraph form [11] which is given as follows:

$$\begin{aligned} &\underset{\mathbf{W}_k \in \mathbb{H}^{N_T}, E_l^s, \phi}{\text{minimize}} \quad \phi + \eta \sum_{k=1}^K \text{Tr}(\mathbf{W}_k) \\ \text{s.t.} \quad &\text{C1: } \frac{\text{Tr}(\mathbf{H}_k \mathbf{W}_k)}{\Gamma_{\text{req}_k}} \geq \sum_{j \neq k}^K \text{Tr}(\mathbf{H}_k \mathbf{W}_j) + \sigma_s^2, \forall k, \\ &\text{C2, C6,} \\ &\text{C3: } P_{C_l} + \varepsilon \sum_{k=1}^K \text{Tr}(\mathbf{B}_l \mathbf{W}_k) \leq E_l^s \beta_l, \forall l, \\ &\text{C4: } \sum_{k=1}^K \text{Tr}(\mathbf{B}_l \mathbf{W}_k) \leq P_l^{\text{Tmax}}, \forall l, \\ &\text{C5: } \mu \left(\sum_{k=1}^K \text{Tr}(\mathbf{W}_k \mathbf{G}_m) \right) \geq P_m^{\text{min}}, \forall m, \\ &\text{C7: } \delta \left(\sum_{k=1}^K \text{Tr}(\mathbf{W}_k \mathbf{B}_l) \rho_k^l R_k \right) \leq \phi, \forall l, \\ &\text{C8: } \mathbf{W}_k \succeq \mathbf{0}, \forall k, \quad \text{C9: Rank}(\mathbf{W}_k) \leq 1, \forall k, \end{aligned} \quad (10)$$

where

$$\mathbf{B}_l \triangleq \text{diag} \left(\underbrace{0, \dots, 0}_{(l-1)N_T}, \underbrace{1, \dots, 1}_{N_T}, \underbrace{0, \dots, 0}_{(L-l)N_T} \right), \forall l \in \{1, \dots, L\},$$

is a block diagonal matrix with $\mathbf{B}_l \succeq \mathbf{0}$. ϕ in the objective function and constraint C7 is an auxiliary optimization variable. Constraints C8, C9, and $\mathbf{W}_k \in \mathbb{H}^{N_T}, \forall k$, are imposed to guarantee that $\mathbf{W}_k = \mathbf{w}_k \mathbf{w}_k^H$ holds after optimization.

Then, we relax constraint C9: $\text{Rank}(\mathbf{W}_k) \leq 1$ by removing it from the problem formulation, such that the considered problem becomes a convex SDP given by

$$\begin{aligned} &\underset{\mathbf{W}_k \in \mathbb{H}^{N_T}, E_l^s, \phi}{\text{minimize}} \quad \phi + \eta \sum_{k=1}^K \text{Tr}(\mathbf{W}_k) \\ \text{s.t.} \quad &\text{C1} - \text{C8}. \end{aligned} \quad (11)$$

We note that the relaxed problem in (11) can be solved efficiently by numerical solvers such as CVX [12]. If the solution

TABLE I
ITERATIVE RESOURCE ALLOCATION ALGORITHM

Algorithm Reweighted l_1 -norm Method

- 1: Initialize the maximum number of iterations L_{max} and a small constant $\kappa \rightarrow 0$
- 2: Set iteration index $n = 0$ and $\rho_k^l(n) = 1, \forall k, l$
- 3: **repeat** {Loop}
- 4: Solve (11) for a given set of $\rho_k^l(n)$ and obtain an intermediate beamforming vector \mathbf{w}_k^l
- 5: Update the weight factor as follows:

$$\begin{aligned} \rho_k^l(n+1) &= \frac{1}{\|\mathbf{w}_k^l\|_2^2 + \kappa}, \forall l, k, \\ n &= n + 1 \end{aligned}$$

6: **until** $n = L_{\text{max}}$

\mathbf{W}_k of (11) is a rank-one matrix, then the problems in (10) and (11) share the same optimal solution and the same optimal objective value. Otherwise, the optimal objective value of (11) serves as a lower bound for the objective value of (10).

Next, we reveal the tightness of the SDP relaxation adopted in (11) in the following theorem.

Theorem 1: Assuming the channel vectors of the IRs, $\mathbf{h}_k, k \in \{1, \dots, K\}$, and the ERs, $\mathbf{g}_m, m \in \{1, \dots, M\}$, can be modeled as statistically independent random variables then the solution of (11) is rank-one, i.e., $\text{Rank}(\mathbf{W}_k) = 1, \forall k$, with probability one.

Proof: Please refer to the Appendix. ■

In other words, whenever the channels satisfy the condition stated in Theorem 1, the optimal beamformer \mathbf{w}_k^* of (10) can be obtained with probability one by performing an eigenvalue decomposition of the solution \mathbf{W}_k of (11) and selecting the principal eigenvector as the beamformer.

C. Iterative Resource Allocation Algorithm

In general, for a fixed weight factor, ρ_k^l , the solution of (10) does not necessarily provide sparsity and the approximation adopted in (9) may not be tight. For improving the obtained solution, we adopt the *Reweighted l_1 -norm Method* which was originally designed to enhance the data acquisition in compressive sensing [10]. The overall resource allocation algorithm is summarized in Table I. In particular, the weight factor ρ_k^l is updated as in line 5 of the iterative algorithm such that the magnitude of beamforming vectors $\|\mathbf{w}_k^l\|_2^2$ with small values are further reduced in the next iteration. As a result, by iteratively updating ρ_k^l and solving (11), a suboptimal beamforming solution with sparsity can be constructed. We note that the iterative algorithm in Table I converges to a local optimal solution of the original problem formulation in (8) for $\kappa \rightarrow 0$ and a sufficient number of iterations [7], [10]. Furthermore, when the primal-dual path-following method [13] is used by the numerical solver for solving (11), the computational complexity of the proposed algorithm is $\mathcal{O}(L_{\text{max}} \max\{N_T L, K + 3L + M\}^4 (N_T L)^{1/2} \log(1/\epsilon))$ for a given solution accuracy $\epsilon > 0$. The computational complexity is significantly reduced compared to the computational complexity of an exhaustive search with respect to K and L , i.e., $\mathcal{O}((2^L - 1)^K \max\{N_T L, K + 3L + M\}^4 (N_T L)^{1/2} \log(1/\epsilon))$.

V. RESULTS

In this section, we evaluate the network performance of the proposed resource allocation design via simulations. There are $L = 3$ RRHs, $K = 5$ IRs, and $M = 2$ ERs in the system.

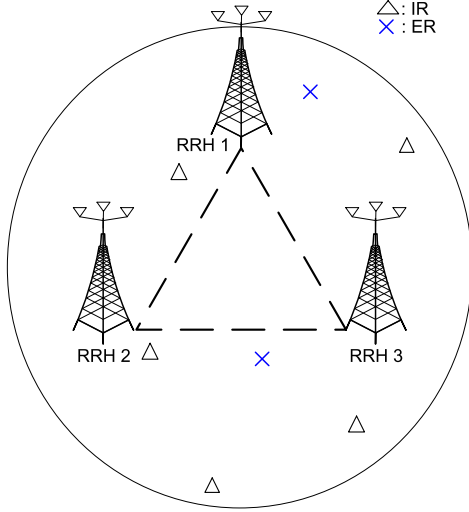
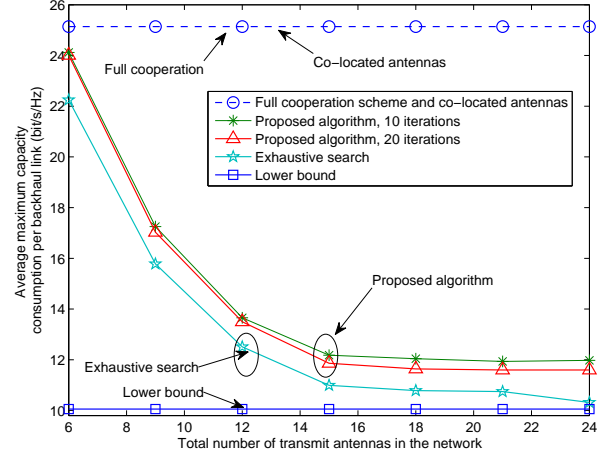


Fig. 2. CoMP network simulation topology with $L = 3$ RRHs, $K = 5$ IRs, and $M = 2$ ERs.

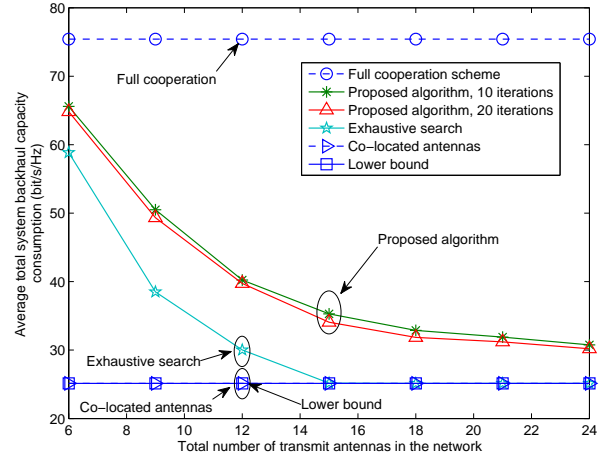
TABLE II
SYSTEM PARAMETERS

Carrier center frequency	1.9 GHz
Path loss exponent	3.6
Multipath fading distribution	Rayleigh fading
Total noise variance, σ_s^2	-23 dBm
Minimum required SINR, $\Gamma_{\text{req},k} = \Gamma_{\text{req}}, \forall k \in \{1, \dots, K\}$	15 dB
Circuit power consumption at CP, $P_{\text{CP}}^{\text{CP}}$	40 dBm
Circuit power consumption at the l -th RRH, P_{C_l}	30 dBm
Max. power supply at the CP, $P_{\text{max}}^{\text{CP}}$	50 dBm
Power amplifier power efficiency	$1/\varepsilon = 0.38$
Max. transmit power allowance, P_l^{Tmax}	46 dBm
Min. required power transfer, P_m^{min}	0 dBm
RF to electrical energy conversion efficiency, μ	0.5
Power loss in transferring power from the CP to RRH, $1 - \beta_l$	0.2

We focus on the network topology shown in Figure 2. The distance between any two RRHs is 500 meters. The three RRHs construct an equilateral triangle while the IRs and ERs are uniformly distributed inside a disc with radius 1000 meters centered at the centroid of the triangle. The simulation parameters can be found in Table II. In the iterative algorithm, we set κ and L_{max} to 0.0001 and 20, respectively. The numerical results in this section were averaged over 1000 independent channel realizations for both path loss and multipath fading. The performance of the proposed scheme is compared with the performances of a full cooperation scheme, an optimal exhaustive search scheme, and a traditional system with co-located transmit antennas. For the full cooperation scheme, the solution is obtained by setting $\delta = 0$, $\eta = 1$, and solving (11) by SDP relaxation. For the exhaustive search, it is expected that multiple optimal solutions for (8) may exist. Thus, for the set of optimal solutions, we further select the one having the minimal total system backhaul capacity consumption. If there are multiple optimal solutions with the same total system backhaul capacity consumption, then we select the one requiring the minimal total network transmit power. As for the co-located transmit antenna system, we assume that there is only one RRH located at the center of the system equipped with the same number of antennas as all RRHs combined in the distributed setting. Besides, the CP is not at the same location as the RRH for the co-located transmit antenna system, i.e., a backhaul is still needed. Furthermore, we set $P_l^{\text{Tmax}} = \infty$ for the co-located



(a) Average maximum capacity consumption per backhaul link.



(b) Average total system backhaul capacity consumption.

Fig. 3. Average backhaul capacity consumption versus total number of transmit antennas in the network for different resource allocation schemes.

transmit antenna system to study its power consumption.

A. Average Backhaul Capacity Consumption

In Figures 3(a) and 3(b), we study the average maximum backhaul capacity consumption per backhaul link and the average total system backhaul capacity consumption, respectively, versus the total number of transmit antennas in the network, for different resource allocation schemes. We set $\delta = 1$ and $\eta = 0$ in (11) for the proposed scheme to fully minimize the maximum capacity consumption per backhaul link. The performance of the proposed iterative algorithm is shown for 10 and 20 iterations. It can be seen from Figure 3(a) that the proposed iterative algorithm achieves a close-to-optimal backhaul capacity consumption in all considered scenarios even for the case of 10 iterations. We note that the gap between the proposed algorithm and the exhaustive search in Figure 3(a) is caused by the sub-optimality of the objective function approximation in (9) and insufficient numbers of iterations. In fact, the superior average maximum system backhaul capacity consumption of the optimal exhaustive scheme in Figure 3(a) compared to the proposed scheme comes at the expense of an exponential computational complexity with respect to the number of IRs and RRHs. On the other hand, the performance gap between

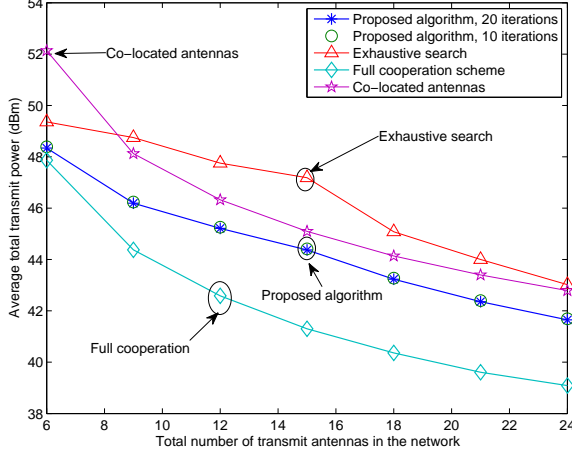


Fig. 4. Average total transmit power (dBm) versus total number of transmit antennas in the network for different resource allocation schemes.

the proposed iterative resource allocation algorithm and the full cooperation scheme/(co-located antennas system) increases as the total number of transmit antennas. In Figures 3(a) and 3(b), we observe that the average backhaul capacity consumption of the proposed algorithm decreases monotonically with an increasing number of antennas and converges to constant values close to the lower bounds, respectively. The lower bounds in Figures 3(a) and 3(b) are given by $\left\lceil \frac{K}{L} \right\rceil \log_2(1 + \Gamma_{\text{req}})$ and $K \log_2(1 + \Gamma_{\text{req}})$, respectively. Indeed, when both the power budget and the number of antennas at the RRHs are sufficiently large, full cooperation may not be beneficial. In this case, conveying the data of each IR to one RRH may be sufficient for providing the QoS requirements for reliable communication and efficient power transfer. Hence, backhaul system resources can be saved. Besides, it can be seen from Figure 3(b) that the system with co-located antennas requires the smallest amount of total system backhaul capacity since the data of each IR is conveyed only to a single RRH. However, the superior performance of the co-located antenna system in terms of total network backhaul capacity consumption incurs the highest capacity consumption per backhaul link among all the schemes, cf. Figure 3(a).

B. Average Total Transmit Power and Harvested Power

In Figure 4, we study the average total transmit power versus total number of transmit antennas for different resource allocation schemes. It can be observed that the total transmit power decreases monotonically with increasing number of transmit antennas. This is due to the fact that the degrees of freedom for resource allocation increase with the number of transmit antennas, which enables a more power efficient resource allocation. Besides, the proposed algorithm consumes a lower transmit power compared to the optimal exhaustive search scheme. This is because the exhaustive search scheme consumes a smaller backhaul capacity at the expense of a higher transmit power. Furthermore, the system with co-located antennas consumes a higher transmit power than the proposed scheme and the full cooperation scheme in all considered scenarios which reveals the power saving potential of CoMP due to its inherent spatial diversity. On the other hand, it is expected that the full cooperation scheme is able to achieve the lowest average total transmit power at the expense of an exceedingly large backhaul capacity consumption, cf. Figure 3.

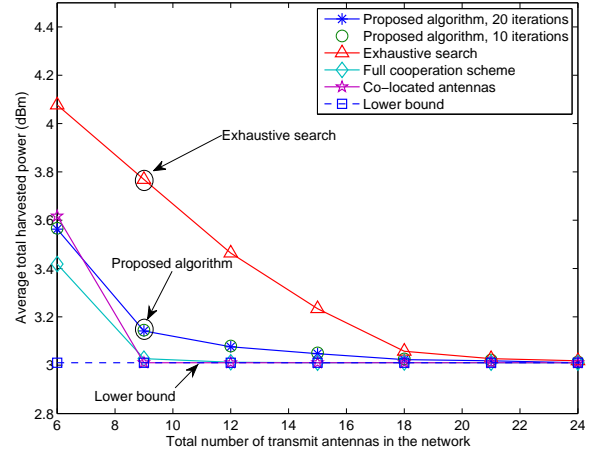


Fig. 5. Average total harvested power (dBm) versus total number of transmit antennas in the network for different resource allocation schemes.

In Figure 5, we study the average total harvested power versus the total number of transmit antennas in the network for different resource allocation schemes. We compare the average total harvested power of all resource allocation schemes with a lower bound which is computed by assuming that constraint C5 is satisfied with equality for all ERs. As can be observed, the total average harvested powers in all considered scenarios are monotonically non-increasing with respect to the number of transmit antennas. This is because the extra degrees of freedom offered by the increasing number of antennas improve the efficiency of resource allocation. In particular, the direction of beamforming matrix \mathbf{W}_k can be more accurately steered towards the IRs which reduces the power allocation to \mathbf{W}_k and the leakage of power to the ERs. This also explains the lower harvested power for the full cooperation scheme and the system with co-located antennas since they both exploit all transmit antennas in the network for joint transmission. On the other hand, the highest amount of radiated power can be harvested for the exhaustive search scheme at the expense of a higher total transmit power.

VI. CONCLUSIONS

In this paper, we studied the resource allocation algorithm design for CoMP multiuser communication systems with SWIPT. The algorithm design was formulated as a non-convex combinatorial optimization problem with the objective to jointly minimize the total network transmit power and the maximum capacity consumption of the backhaul links. The proposed problem formulation took into account QoS requirements for communication reliability and power transfer. A suboptimal iterative resource allocation algorithm was proposed for obtaining a locally optimal solution of the considered problem. Simulation results showed that the proposed suboptimal iterative resource allocation scheme performs close to the optimal exhaustive search scheme and provides a substantial reduction in backhaul capacity consumption compared to full cooperation. Besides, our results unveiled the potential power savings enabled by CoMP networks compared to centralized systems with multiple antennas co-located for SWIPT.

APPENDIX-PROOF OF THEOREM 1

It can be verified that (11) satisfies Slater's constraint qualification and is jointly convex with respect to the optimization

variables. Thus, strong duality holds and solving the dual problem is equivalent to solving the primal problem [11]. For the dual problem, we need the Lagrangian function of the primal problem in (11) which is given by

$$\mathcal{L}\left(\mathbf{W}_k, E_l^s, \phi, \mathbf{Y}_k, \psi_l, \xi_k, \tau_m, \lambda, \omega_l, \theta_l, \chi_l\right) \quad (12)$$

$$= \sum_{k=1}^K \text{Tr}(\mathbf{A}_k \mathbf{W}_k) - \sum_{k=1}^K \text{Tr}\left(\mathbf{W}_k \left(\mathbf{Y}_k + \frac{\xi_k^* \mathbf{H}_k}{\Gamma_{\text{req}_k}}\right)\right) + \Delta$$

where

$$\mathbf{A}_k = \mathbf{D}_k + \sum_{j \neq k} \xi_j \mathbf{H}_j - \mu \sum_{m=1}^M \tau_m \mathbf{G}_m, \quad (13)$$

$$\mathbf{D}_k = R_k \delta \sum_{l=1}^L \mathbf{B}_l \rho_l^k \chi_l + \eta \mathbf{I}_{N_T} + \sum_{l=1}^L (\psi_l + \theta_l) \varepsilon \mathbf{B}_l, \text{ and} \quad (14)$$

$$\Delta = \phi + \lambda(P_C^{\text{CP}} + \sum_{l=1}^L E_l^s - P_{\text{max}}^{\text{CP}}) + \sum_{m=1}^M \tau_m P_m^{\text{min}} - \sum_{l=1}^L \omega_l E_l^s$$

$$+ \sum_{k=1}^K \xi_k \sigma_s^2 + \sum_{l=1}^L \left[\psi_l (P_{C_l} - E_l^s \beta_l) - \theta_l P_l^{\text{Tmax}} - \chi_l \phi \right]. \quad (15)$$

Here, Δ denotes the collection of terms that only involve variables that are independent of \mathbf{W}_k . \mathbf{Y}_k is the dual variable matrix for constraint C8. $\xi_k, \lambda, \psi_l, \theta_l, \tau_m, \omega_l$, and χ_l are the scalar dual variables for constraints C1–C7, respectively.

Then, the dual problem of (11) is given by

$$\begin{aligned} & \underset{\substack{\psi_l, \xi_k, \tau_m, \chi_l \geq 0 \\ \theta_l, \lambda, \omega_l \geq 0, \mathbf{Y}_k \succeq \mathbf{0}}} \text{maximize} \quad \underset{\substack{\mathbf{W}_k \in \mathbb{H}^{N_T} \\ E_l^s, \phi}} \text{minimize} \quad \mathcal{L}(\mathbf{W}_k, E_l^s, \phi, \mathbf{Y}_k, \psi_l, \xi_k, \tau_m, \lambda, \omega_l, \theta_l, \chi_l) \end{aligned} \quad (16)$$

subject to $\sum_{l=1}^K \chi_l = 1$. For the sake of notational simplicity, we define $\Upsilon^* \triangleq \{\mathbf{W}_k^*, E_l^{s*}, \phi^*\}$ and $\Xi^* \triangleq \{\mathbf{Y}_k^*, \psi_l^*, \xi_k^*, \tau_m^*, \lambda^*, \omega_l^*, \theta_l^*, \chi_l^*\}$ as the set of optimal primal and dual variables of (11), respectively. Now, we consider the following Karush-Kuhn-Tucker (KKT) conditions which are useful in the proof:

$$\mathbf{Y}_k^* \succeq \mathbf{0}, \tau_m^*, \psi_l^*, \xi_k^* \geq 0, \forall k, \forall m, \forall l, \quad (17)$$

$$\mathbf{Y}_k^* \mathbf{W}_k^* = \mathbf{0}, \quad (18)$$

$$\mathbf{Y}_k^* = \mathbf{A}_k^* - \xi_k^* \frac{\mathbf{H}_k}{\Gamma_{\text{req}_k}}, \quad (19)$$

where \mathbf{A}_k^* is obtained by substituting the optimal dual variables Ξ^* into (13). $\mathbf{Y}_k^* \mathbf{W}_k^* = \mathbf{0}$ in (18) indicates that for $\mathbf{W}_k^* \neq \mathbf{0}$, the columns of \mathbf{W}_k^* are in the null space of \mathbf{Y}_k^* . Therefore, if $\text{Rank}(\mathbf{Y}_k^*) = N_T L - 1$, then the optimal beamforming matrix $\mathbf{W}_k^* \neq \mathbf{0}$ must be a rank-one matrix. We now show by contradiction that \mathbf{A}_k^* is a positive definite matrix with probability one in order to reveal the structure of \mathbf{Y}_k^* . Let us focus on the dual problem in (16). For a given set of optimal dual variables, Ξ^* , power supply variables, E_l^{s*} , and auxiliary variable ϕ^* , the dual problem in (16) can be written as

$$\underset{\mathbf{W}_k \in \mathbb{H}^{N_T}}{\text{minimize}} \quad \mathcal{L}(\mathbf{W}_k, \phi^*, E_l^{s*}, \mathbf{Y}_k^*, \psi_l^*, \xi_k^*, \tau_m^*, \lambda^*, \omega_l^*, \theta_l^*, \chi_l^*). \quad (20)$$

Suppose \mathbf{A}_k^* is not positive definite, then we can choose $\mathbf{W}_k = r \mathbf{w}_k \mathbf{w}_k^H$ as one of the optimal solutions of (20), where $r > 0$ is a scaling parameter and \mathbf{w}_k is the eigenvector corresponding to one of the non-positive eigenvalues of \mathbf{A}_k^* . We substitute

$\mathbf{W}_k = r \mathbf{w}_k \mathbf{w}_k^H$ into (20) which leads to

$$\underbrace{\sum_{k=1}^K \text{Tr}(r \mathbf{A}_k^* \mathbf{w}_k \mathbf{w}_k^H)}_{\leq 0} - r \sum_{k=1}^K \text{Tr}\left(\mathbf{w}_k \mathbf{w}_k^H \left(\mathbf{Y}_k^* + \frac{\xi_k^* \mathbf{H}_k}{\Gamma_{\text{req}_k}}\right)\right) + \Delta. \quad (21)$$

On the other hand, since the channel vectors of \mathbf{g}_m and \mathbf{h}_k are assumed to be statistically independent, it follows that by setting $r \rightarrow \infty$, the term $-r \sum_{k=1}^K \text{Tr}\left(\mathbf{w}_k \mathbf{w}_k^H \left(\mathbf{Y}_k^* + \frac{\xi_k^* \mathbf{H}_k}{\Gamma_{\text{req}_k}}\right)\right) \rightarrow -\infty$ and the dual optimal value becomes unbounded from below. Besides, the optimal value of the primal problem is non-negative for $\Gamma_{\text{req}_k} > 0$. Thus, strong duality does not hold which leads to a contradiction. Therefore, \mathbf{A}_k^* is a positive definite matrix with probability one, i.e., $\text{Rank}(\mathbf{A}_k^*) = N_T L$.

By exploiting (19) and a basic inequality for the rank of matrices, we have

$$\begin{aligned} & \text{Rank}(\mathbf{Y}_k^*) + \text{Rank}\left(\xi_k^* \frac{\mathbf{H}_k}{\Gamma_{\text{req}_k}}\right) \\ & \geq \text{Rank}\left(\mathbf{Y}_k^* + \xi_k^* \frac{\mathbf{H}_k}{\Gamma_{\text{req}_k}}\right) = \text{Rank}(\mathbf{A}_k^*) = N_T L \\ & \Rightarrow \text{Rank}(\mathbf{Y}_k^*) \geq N_T L - \text{Rank}\left(\xi_k^* \frac{\mathbf{H}_k}{\Gamma_{\text{req}_k}}\right). \end{aligned} \quad (22)$$

Thus, $\text{Rank}(\mathbf{Y}_k^*)$ is either $N_T L - 1$ or $N_T L$. Furthermore, $\mathbf{W}_k^* \neq \mathbf{0}$ is required to satisfy the minimum SINR requirement of IR k in C1 for $\Gamma_{\text{req}_k} > 0$. Hence, $\text{Rank}(\mathbf{Y}_k^*) = N_T L - 1$ and $\text{Rank}(\mathbf{W}_k^*) = 1$ hold with probability one. In other words, the optimal joint beamformer \mathbf{w}_k^* can be obtained by performing eigenvalue decomposition of \mathbf{W}_k^* and selecting the principal eigenvector as the beamformer.

REFERENCES

- [1] P. Grover and A. Sahai, "Shannon Meets Tesla: Wireless Information and Power Transfer," in *Proc. IEEE Intern. Sympos. on Inf. Theory*, Jun. 2010, pp. 2363–2367.
- [2] R. Zhang and C. K. Ho, "MIMO Broadcasting for Simultaneous Wireless Information and Power Transfer," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 1989–2001, May 2013.
- [3] D. W. K. Ng, E. S. Lo, and R. Schober, "Wireless Information and Power Transfer: Energy Efficiency Optimization in OFDMA Systems," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 6352–6370, Dec. 2013.
- [4] D. Lee, H. Seo, B. Clerckx, E. Hardouin, D. Mazzarese, S. Nagata, and K. Sayana, "Transmission and Reception in LTE-Advanced: Deployment Scenarios and Operational Challenges," *IEEE Commun. Magazine*, vol. 50, pp. 148–155, Feb. 2012.
- [5] R. Irmer, H. Droste, P. Marsch, M. Grieger, G. Fettweis, S. Brueck, H. P. Mayer, L. Thiele, and V. Jungnickel, "Coordinated Multipoint: Concepts, Performance, and Field Trial Results," *IEEE Commun. Magazine*, vol. 49, pp. 102–111, Feb. 2011.
- [6] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-Efficient Resource Allocation in Multi-Cell OFDMA Systems with Limited Backhaul Capacity," *IEEE Trans. Wireless Commun.*, vol. 11, pp. 3618–3631, Oct. 2012.
- [7] J. Zhao, T. Quek, and Z. Lei, "Coordinated Multipoint Transmission with Limited Backhaul Data Transfer," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 2762–2775, Jun. 2013.
- [8] B. Dai and W. Yu, "Sparse Beamforming for Limited-Backhaul Network MIMO System via Reweighted Power Minimization," in *Proc. IEEE Global Telecommun. Conf.*, Dec. 2013.
- [9] D. Donoho, "Compressed Sensing," *IEEE Trans. Inf. Theory*, vol. 52, pp. 1289–1306, Apr. 2006.
- [10] E. Candès, M. B. Wakin, and S. P. Boyd, "Enhancing Sparsity by Reweighted l_1 Minimization," *Journal of Fourier Analysis and Applications*, vol. 14, pp. 877–905, Aug. 2008.
- [11] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.
- [12] M. Grant and S. Boyd, "CVX: Matlab Software for Disciplined Convex Programming, version 2.0 Beta," [Online] <https://cvxr.com/cvx>, Sep. 2013.
- [13] Z.-Q. Luo, W.-K. Ma, A.-C. So, Y. Ye, and S. Zhang, "Semidefinite Relaxation of Quadratic Optimization Problems," *IEEE Signal. Process. Magazine*, vol. 27, pp. 20–34, May 2010.